Understanding Decision Making Drivers and Mechanisms in a Transition towards low emission Transportation Mode Choices: An agent-based modelling approach

Master Thesis

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Layman Abstract

Which transportation modes people use impacts how sustainable a country or a population can be. To get more people to travel with more sustainable transportation modes, e.g. public transport or a bike, it is important to understand the reasons and dynamics that contribute to the transportation mode choices that people currently make. This paper explored these dynamics through agent-based modelling.

In agent-based modelling it is possible to create agents with a range of characteristics, e.g. their transportation mode attitudes and preferences, whether they own a driver's license and car, what other agents are in their social network, etc… These agents are then given behaviour rules based on empirical findings and data to simulate their decision-making processes. In our model, agents make decisions based on their preferences and their preferences are influenced over time depending on how crowded they perceive the mode their chose, what modes their social circle chooses, and what attitudes they have towards the transportation modes. Diversifying the rules of the model or the input characteristics that agents receive allows exploring which dynamics lead to more sustainable findings. These findings can then be used to inform future research and policy making on which circumstances would, under the assumptions of the model, lead to the desired increase in the number of people using sustainable transportation modes.

Our findings suggest that when people are more sensitive to how soon they perceive a transportation mode as crowded, they use the car less overall. While it is difficult to influence how sensitive people are, it is possible to adjust the capacity that the infrastructure of the transportation mode has. For example, more and wider bike lanes or longer trams travelling with higher frequency would make it less likely that they are perceived as crowded, because less people would use that specific bike lane or tram. Decisions on what transportation mode infrastructure to invest in are therefore crucial to steer people toward more sustainable transportation choices. We also find that social norms can spread the use of car alternatives, but that they require a certain popularity to be spread by social norms. It may need other approaches to popularize less used car alternatives initially.

Abstract

Passenger transportation is a significant contributor to global greenhouse gas emissions. Transportation modes (TMs) that individuals choose in daily life differ in their emissions, and a shift towards more sustainable TM usage on a societal scale is desirable. However, many people still utilize high-emission options, such as traveling by car.

Here, we present an agent-based model simulating TM choices over time. We implement decision-making mechanisms based on psychological theory on influences of social norms, environmental affordances, and internal attitudes. A sensitivity analysis is applied to explore which interplay of mechanisms could facilitate a transfer towards lower-emission TM choices.

Our results indicate that, while the car is the most dominant mode at the start of the model, the model stabilizes with public transportation and car usage counts being even. Less popular TMs such as biking and carsharing decrease in popularity. Sensitivity analysis on the impact of social influence, experience of crowdedness, and internal attitudes indicates that lower tolerance towards crowdedness is the most relevant factor in reducing car usage.

Our findings implicate that frequent crowdedness perception might be a key factor in reducing car usage, which could be relevant for policy development around reducing the infrastructure capacities of undesirable TMs. We further conclude that for social norms to have a positive effect on TM usage, the TM requires an initial popularity. Increasing societal acceptance of less popular car alternatives might require complementary approaches in popularizing the TM before the effects of social norms can apply.

Keywords: sustainable transportation, social norm internalization, agent-based modelling, sensitivity analysis

Contents

Introduction

The passenger transportation sector has a large impact on global greenhouse gas emissions, thereby making it an area of interest in efforts to mitigate climate change. Cars alone are estimated to cause 450 tons of CO_2 emissions per year (European Commission & Transport & Environment, 2022). However, lower-emission transportation modes (TMs) are available. While cars are estimated to produce about 170g of CO_2/km per passenger, buses emit 97g, trams 29g (UK Government, 2022), and cycling only 16g (European Cyclists Federation, 2013). Despite these differences, cars are still the most popular mode of transport, accounting for 79.7% of passenger-kilometres travelled in the EU (Eurostat, 2021). These figures highlight the potential for reducing CO_2 emissions by encouraging the use of lower-emission TMs. Therefore, to combat climate change, a societal shift of TM choices from car usage to more eco-friendly options would be desirable.

To facilitate such a transition, it is crucial to identify the underlying dynamics that motivate people's TM choices. Many theories exist on how attitudes are shaped, intentions are formed, and how those may lead to adaptations in behaviour. However, less is known about how such dynamics develop in practice when the system is complex, and many factors interact. Agent-based modelling (ABM) has been proposed to model such complex interactions over time. Jager (2021) discusses the potential of ABMs to explore climate-related behavioural dynamics. He reasons for the potential of ABMs because simple behaviour rules for interaction between agents can lead to complex and sometimes surprising outcomes. In the context of pro-environmental behaviour, ABMs enable the study of dynamic interactions that could lead to desirable outcomes, such as increased pro-environmental actions. Modelling such dynamic interactions is especially beneficial when the decisions of others influence the development of behaviours such as dietary preferences (e.g. veganism) or modality choice (e.g. cycling; Jager, 2021).

In this paper, we present an extension of the TransportTransform ABM developed by Köckritz et al. (2023) on individual transportation mode (TM) choices. In their model, the authors explore the development of TM choices while being affected by social norms and mode crowdedness. We extend the model by implementing dynamic changes in TM preferences over time as a learning mechanism and by integrating individuals' internal attitudes towards TMs into their learning process.

Theoretical Background on Model Extensions

In the context of passenger transportation, we argue that the main drivers of modality choice are an individual's physical environment, their social environment, and their internal values. The physical environment is relevant because it can strongly influence the range of modality options an individual perceives and how they evaluate them. Kaaronen and Strelkovskii (2020) reason for this dynamic with the theory of affordances. Originally published by Gibson (1979), affordance theory suggests that objects in our environment afford a set of actions to an organism. This set of actions is determined by the shape of the object and the perception of the organism. For example, a chair ‘affords’ sitting to a human being, or a door handle ‘affords’ to be pushed or pulled. Gibson (1979) argues that these perceptions happen without much cognitive effort and that the ‘affordances’ of objects thereby guide our behaviour. Kaaronen and Strelkovskii (2020) take this approach to a macro level and apply it to pro-environmental behaviour that an individual’s physical environment affords. For example, the quality of bike lane infrastructure or how crowded public transportation is may determine whether a person perceives these transportation modes as an option and how they appraise these options. If the physical environment does not facilitate the use of lower-emission TMs, people may be less inclined to consider these TMs. “There is only so much that individuals can do if sufficient opportunities for behaving sustainably do not exist” (Kaaronen and Strelkovskii, 2020, p. 85). The environment can thereby enable pro-environmental behaviour, while a lack of pro-environmental affordances could cause a gap between environmentally friendly intention and behaviour (Kaaronen & Strelkovskii, 2020)

Social influence is another key driver for decision-making. People’s behaviour can greatly be influenced by social influence (Miller & Prentice 1996; Cialdini & Goldstein, 2004). Most people are part of social groups with whom they interact regularly and will adjust their behaviours to the group norms to reinforce their belonging to the group (e.g. Warner et al., 2022). People may also perceive pressure from their social environment and adjust their behaviour to comply (Cialdini & Goldstein, 2004). These are cases of external motivation, in which individuals follow social norms because they fear punishment or anticipate rewards from their social environment. However, over time, individuals often internalise the social norms of the group, a concept called social norm internalisation. They will then follow the norm because it is an intrinsically desired personal goal, independently of any anticipated reward or punishment from their social environment (Aronfreed, 1968; Andrighetto, Villatoro, & Conte, 2010; Gintis, 2016). Individuals also differ on how influenceable they are by their social environment and may be more likely to seek and adopt a group opinion if they are less certain about their individual stance (Spears, 2021). These findings suggest that individuals will adopt a social norm as their own after extended exposure and that people differ in how influenceable they are, depending on how certain they are about their own position.

In the context of TM choices, several psychological frameworks have been proposed. De Vos et al. (2022) present an application of the *Theory of interpersonal behaviour* (Triandis, 1977) and the *model of goal-directed behaviour* (Perugini & Bagozzi, 2001) in the context of TM choices. Both theories discuss the relevance of social norms in intention formation. Beyond social influence, attitudes and satisfaction are considered key drivers of intention. In line with these theories, negative experiences with TMs would decrease satisfaction and thereby decrease TM use intention. We base our model extensions on these theories to model social norms, internal attitudes, and TM satisfaction as key decision-making drivers in TM choices.

Model Extensions

Given the theoretical frameworks above, we present a theory-driven ABM in which agents, in line with Köckritz et al. (2023), choose TMs based on their preferences, the choices in their social environment, and the perceived affordances of their physical environment. In extension to Köckritz et al. (2023), agents dynamically update their preferences: (dis)satisfaction with TM usage influences their preferences and agents internalize social norms. We also implement internal attitudes towards TMs, based on empirical data on attitudes towards TMs from Wolf & Schröder (2019), to moderate the effect of external experiences on agents' preferences. Finally, an extensive sensitivity analysis is performed to investigate how model inputs and dynamics affect model outcomes.

With our model extensions, we aim to further explore the underlying mechanisms in TM choice. In the context of the need for more sustainable transportation, we are especially interested in what dynamics and circumstances lead to model outcomes in which agents use more sustainable transportation, such as bikes or public transportation. Given the context of everyday transportation, this ultimately results in the reduction of car usage. With our extensions, we aim to answer the following research question:

> *What (combination of) dynamics and circumstances could lead to lower car usage in everyday transportation and increase the adoption of lower-emission transportation modes such as biking, public transportation, or carsharing?*

Methods

The model extension builds on the agent-based model on transportation choice developed by Köckritz et al. (2023). Further data was used from the dataset provided by Wolf & Schröder (2019). The model is described following the ODD protocol standard for agent-based modelling for human decisions (Grimm et al., 2006; Grimm et al., 2010; Grimm et al., 2020). The ODD protocol describes the model by Köckritz et al. (2023) with our extensions integrated. A detailed outline of the changes and additions made can be found in Appendix A.

ODD Protocol

1. Purpose and patterns

The purpose of the model is to explore dynamics of decision making and how they could lead to more sustainable transportation choices. Agents represent people who make decisions about daily transportation modes based on internal attitudes, influence of their social network, and experiences and limitations of their physical environment. Understanding the interaction of these decision-making drivers and how more sustainable choices are achieved in the model informs hypothesis for experimental research as well as policy making in a transition to a low emission mobility future.

2. Entities, state variables and scales

The main entity of the model are agents, which each represent a human being who chooses TMs. Agents have attributes which influence their decisions. For each available TM agents have a weight that determines their chance of picking that TM. Agents also have a habit cycle, which determines after how many model steps they reconsider their current TM. Two other attributes describes whether the agent owns a car and drivers' licence, respectively, which determine the available TMs of the agent. Finally, agents have attributes describing their attitude towards each TM. An overview on (global) model parameters and agent parameters can be found in Table 1 and Table 2, respectively.

Two other entities are the social network and the environment in which agents make decisions. The social network determines which agents have social connections with each other and thereby what subgroup of agents apply social influence on an agent. The environment is shaped by the global usage of TMs which influence agents experience of crowdedness.

Table 1

Global Model Parameters

Name	Description	Range / Options
Soc_midpoint	Proportion of social circle using one TM , at which the agent has a 50% of experiencing social influence (midpoint of sigmoid function)	0.3 - 0.7
Crowded_midpoint	Proportion of agents using the same TM gloablly, at which the agent has a 50% of experiencing crowdedness (midpoint of sigmoid function)	0.3 - 0.7
Crowdedness _influence	How much the TM_weight decreases when the agent experiences crowdedness	0.0 - 0.3
Social _Influence	How much the tm_weight increases when an agent experiences social influence	0.0 - 0.3
Tmp_impact	How strong an agent's attitude (tmp score) affects how much an agent is influenced by crowdedness or social influence	1 - 5

Note[1]. All global parameters are static, have the data type float, and are initialised based on model input.

Table 2

Agent parameters

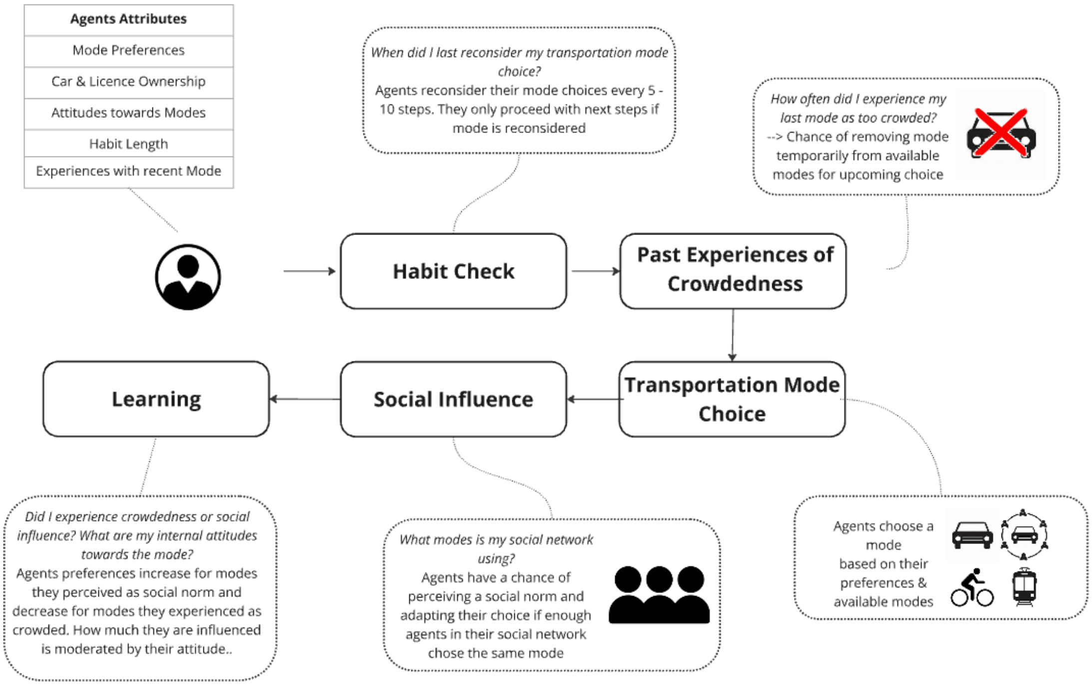
Name	Description	Static / Dynamic	Data type	Initialised based on	Range / Options
tm_weights	Holds the weights determining the chance an agent has of picking each TM.	dynamic	Dic {str:float}	Empirical data	0,27
car_owner	Whether the agent owns a car.	Static	Bool	Empirical data	True, false
License	Whether the agents has a drivers license	Static	Bool	Empirical data	True, false
Available_modes	The TMs available to the agent	Static	List	Car ownership and license	Car, Bike, PT, Carsh
Tmp	Holds the internal attitude an agent has towards each TM	Static	Dic {str:float}	Empirical data	-120 - 120
Habit	The time an agent sticks to a chosen habit,	Static	Int	Stochasticity	5 - 10
Habit_next	The number of model steps left until the agent reconsiders their TM	Dynamic	Int	Model events	0 - 10
Main_mode	The TM the agent currently uses	Dynamic	Str	Stochasticity	Car, Bike, PT, Carsh
experiences	Experiences of crowdedness the agent had since they last re-considered their TM	Dynamic	[int]	Model events	-1,1

3. Process overview and scheduling

During the initialisation of the model, the agent's social network is created an all attributes are initialised. Afterwards, each model step can be described with 5 phases: *habit check, past experience check, TM choice, social influence,* and *learning.* An overview of the phases is shown in Figure 1.

Figure 1

Agents' Decision-Making Process during a Model Step



Note. The figure shows the phases an agent goes through each step of the model.

Habit Check

The agents 'check' whether their habit cycle has come to an end (habit_next = 0). Only agents for whom this applies continue with the following steps.

Past Experience

Agents evaluate the experience with the mode they last chose. If the number of negative experiences outweigh non-negative experiences, the mode will not be available during the next step TM choice.

TM choice

The agent chooses their next TM based on their available modes with probabilities defined by the agents tm_weights.

Social Influence

Agents check which TM was most chosen by agents in their social network. If the proportion of agents who chose that TM exceeds the value of Soc_threshhold, the agent has a chance of 80% of adapting their chosen TM to the social norm.

Learning

The agent's weights are permanently changed based on their experience of crowdedness and social influence. If they experienced crowdedness, the agent's weight for the TM experienced as crowded is reduced based on Crowdedness influence and tmp_impact. Similarly, if they experienced social influence, their weight of the affected TM increases based on social_influence and tmp_impact.

4. Design concepts

4.1. Basic Principles Agents choose TMs based on their available modes and their preferences but are susceptible to choices in their network. Decisions in the network represent social norms and the agents adaptation of their own TM preferences upon experiencing social influence represents the effect of social norm internalisation. Affordances of the environment are modelled as the capacities that TMs have, arguing that lower capacities (e.g. less bike lanes, more crowded public transportation) lead to less perception of TM availability and lower appraisal. Agents are therefore susceptible to experience of crowdedness, with negative experiences decreases the agents preferences for the affected TM. How susceptible agents are to both social influence and crowdedness depends on their internal attitudes.

4.2. Emergence The variety of outcomes under certain conditions, specifically outcomes in which car is not the dominant TM.

4.3. Adaptation Agents have a distribution of weights, which determine the chances for them to pick each TM. Agents adapt to *crowdedness experience* by avoiding a TM if their experience with that TM was negative during their last habit cycle. Agents also can experience *social influence* which would lead them to adapting their choice to the socially dominant TM. Finally, both *crowdedness experience* and *social influence* of a given TM both permanently affect the agents weights for the respective TM.

4.4. Objectives Not applicable.

4.5. Learning *Crowdedness experience* and *social influence* of a given TM both permanently affect the agent's weights for the respective TM. If *crowdedness experience* is present, the weight of the TM that was crowded gets multiplied by $1 - c$. with c being a parameter *crowdedness influence* (default is $c = 0.05$). Thereby a slight decrease in the agent's internal attitude based on their experience is modelled and the agent's chance of choosing that TM in the future is reduced. Similarly, presence of *social influence* leads to an improvement of the agent's internal attitude towards the TM and the affected weight gets multiplied by $1 + s$, with s being a parameter *social influence* (default is $s = 0.05$) to permanently increase the chances of the TM being picked by the agent.

4.6. Prediction Not applicable.

4.7. Sensing Perception of social norms, further explained in section 4.3 and in section 7.

4.8. Interaction Indirect interaction as agents 'observe' other agents decisions and potentially adapt their decisions and preferences.

4.9. Stochasticity Multiple phases of the model involve stochasticity. The agents' habit cycle length is determined based on stochasticity, and agents' TM choices and their perception of social influence and crowdedness involve stochasticity as well. Details are described in Section 7 Submodels.

4.10. Collectives Social networks influencing the agents perception of social norms.

4.11. Observation Each model steps stored the number of TMs chosen and the numbers of agents that perceived *social influence* and *crowdedness*.

5. Initialization

The agent network is created using a Watts-Strogatz small-world network (Watts & Strogatz, 1998; Strogatz, 2001). Agents' initial preferences and *TM attitudes* are based on reports on the usage frequency of different TMs and attitude scores in the empirical data by Wolf & Schröder (2019; see Section 6). Neither *social influence* nor *crowdedness experience* are present at t=0.

6. Input data

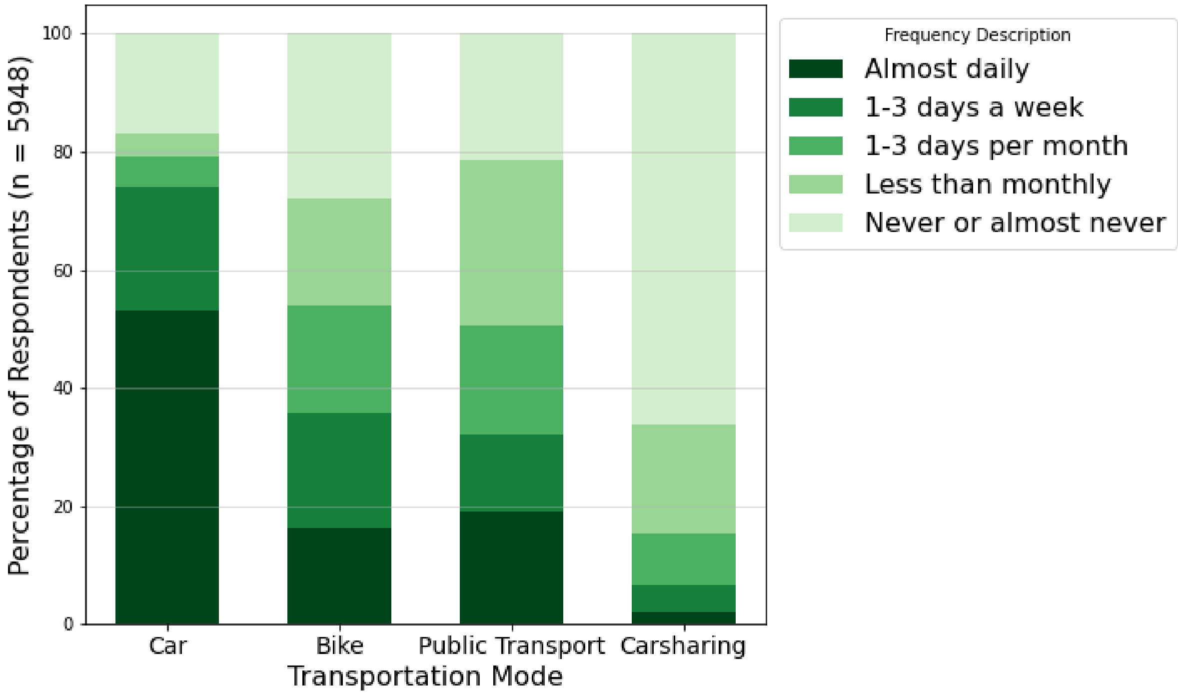
The data provides answers from $n = 5948$ respondents about their usage and attitudes towards transportation modes, including innovative transportation modes (e.g. autonomous driving). The data utilized for our model were information on how frequently respondents use the TMs *car, bike, PT,* and *carsharing*, and whether respondents had a driver's license and owned a car. Further data included information on how respondents prioritized different values associated with transportation (e.g. safety, cost efficiency…) and how they rated the TMs on these values.

85.81% reported having a license, enabling them to use the TM carsharing, and 77.08% reported having both a car and a license, enabling them to use both TMs carsharing and car.

TM use was highest for *car*, followed by *bike* and *public transport*. 74% of respondents use the car at least once a week and 53% every day. Public transport is used at least once a week by 32% of respondence and 19% every day. For biking, these numbers are 36% and 16%, respectively. The TM use frequencies are shown in Figure 2 in more detail.

Figure 2

Transportation Mode Frequencies

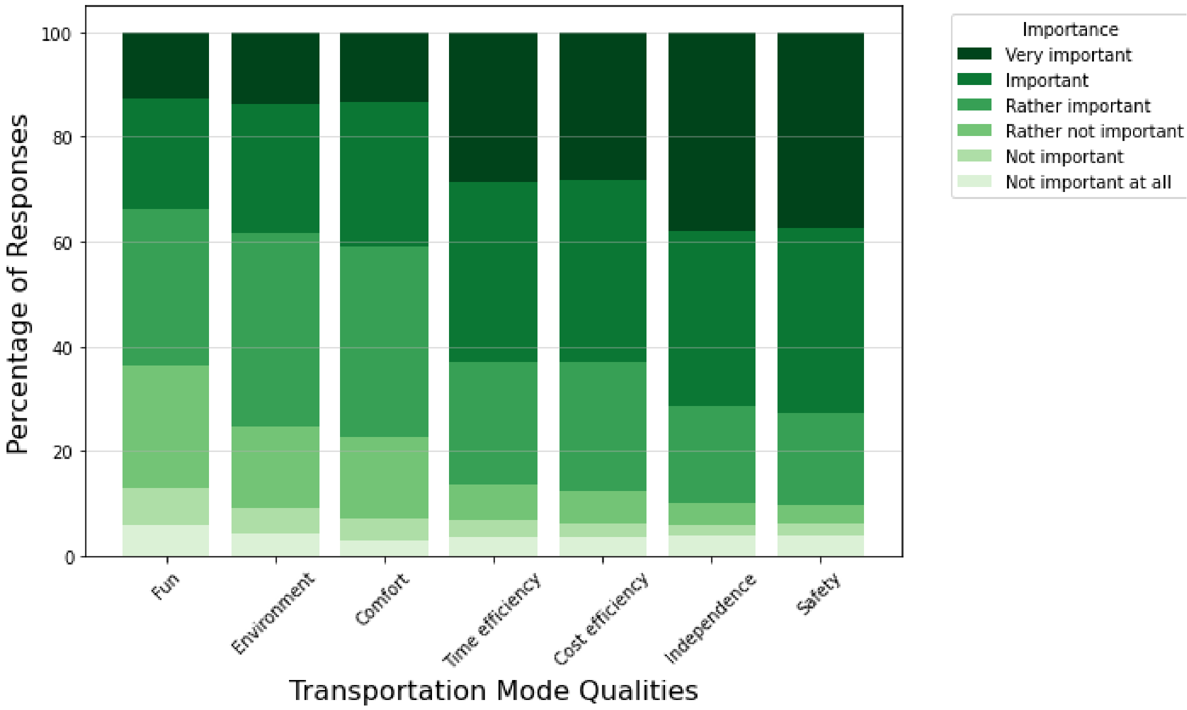


Transportation modes are shown on the X axis. The colour scale indicates the reported frequency. The frequencies of responses are shown on the Y axis in %.

Importance of transportation mode qualities was assessed with a 1-6 Likert scale from not important at all – very important on 7 dimensions: *independence, comfort, cost efficiency, environmental friendliness, safety,* and *fun. Safety* and *independence* were considered most important with >37% of respondents rating each as 'very important'. *Fun* was considered least important, with only 13% considering this 'very important'. Details on the distribution of importance ratings on transportation mode qualities is shown in Figure 3.

Figure 3

Importance of Transportation Mode Qualities

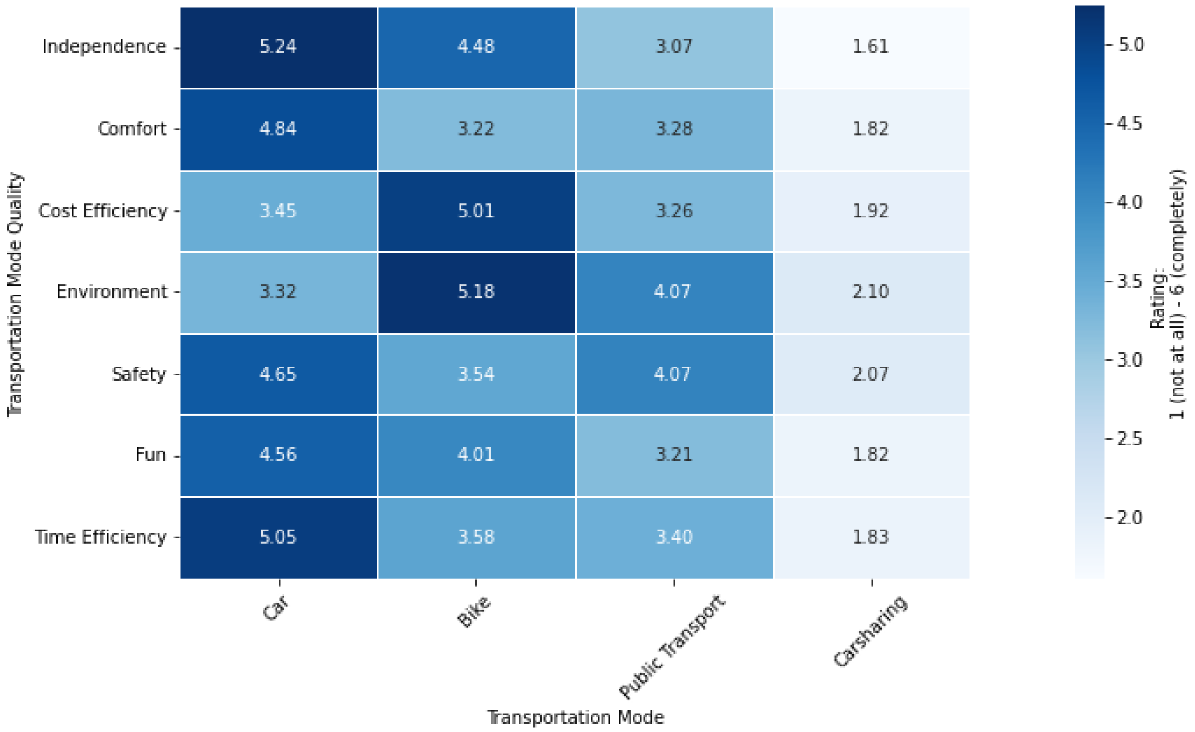


The different TM qualities are shown on the X axis and are sorted by importance. The colour scale represents the rated importance of each TM quality. The frequencies of each response are shown on the Y axis in %.

Survey respondents also rated how much they feel that each transportation mode fulfilled their needs on each quality on a 1-6 Likert scale from *not at all – completely.* On average, *bike* is rated highest on *cost efficiency* (M = 5.01) and *environmental friendliness* (M = 5.16). *Car* is rated highest on the remaining qualities *independence* (M = 5.24), *comfort* (M = 4.84), *safety* (M = 4.85), *fun* (M = 4.56), and *time efficiency (M = 5.05). Public Transport* mean ratings range from 3.07 (*independence)* to M = 4.07 (*environmental friendliness & safety).* Carsharing *has the lowest scores overall, ranging from* M *= 1.61 (independence*) to M = 2.10 (*environment).* More details on TM ratings are displayed in Figure 4.

Figure 4

Mean TM Quality Ratings of Individual TMs



X axis shows the different TMs, Y axis shows the different TM qualities. Numbers and colour scale in the grid show the average rating of how much the TM fulfils the TM quality need on a scale from 1 (not at all) – 6 (completely).

With the respondents rating of each TM quality on each TM and their perceived importance of each TM quality, a utility score *transportation mode potential (TMP)* was developed to quantify an agent's attitude towards each transportation mode:

$$TMP_{TM} = \sum_{TM\ Qualities} Imporance_{TM\ Quality} * Rating_{TM}$$

With

TM Qualities being the 7 TM qualities,

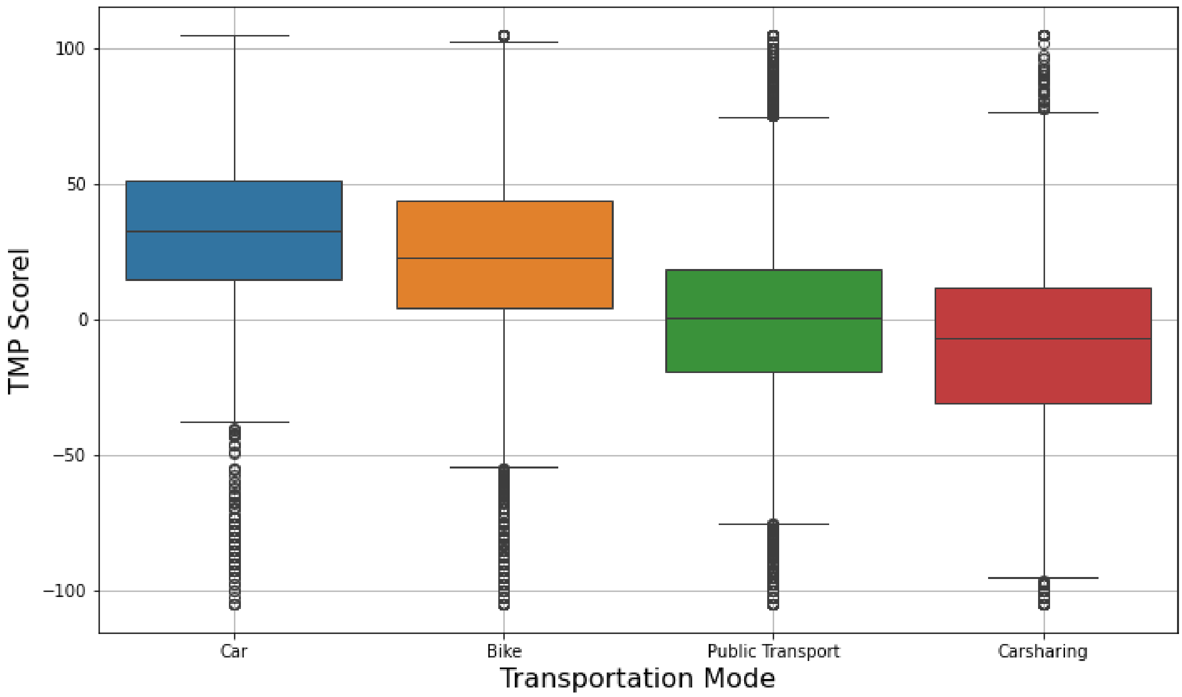
$Importance_{TM\ Quality}$ being the rated importance of the respective TM quality, and

$Rating_{TM}$ being the rating how the TM was assessed on the respective TM quality.

In this computation, each TM quality rating is weighted by how important the TM quality is perceived. The sum of weighted qualities yields the TMP score as a measure of the agent's attitude towards the TM. The distribution of TMP scores on each TM is shown in Figure 5.

Figure 5

Distribution of TMP scores per TM



Y axis shows the TMP score, X axis shows the respective TM.

7. Submodels

The submodels described in the 'process overview and scheduling' section are explained in more detail.

Habit Check

Agents have a habit cycle with length five to ten which indicates how often they reconsider their TM choices. The cycle length of each agent gets determined randomly at the initialisation of the model, as well as how far they are away from reconsidering TMs for the first time. Agents have an attribute *habit_next* which is initialised randomly as a number between 0 and their habit cycle length, decreases by 1 with each model step, and gets reset to the agent's habit length after reaching 0. Only when *habit_next* = 0 will the agent go through the other model phases and thereby reconsider his decision.

The habit cycle was implemented to represent heterogeneity in people's frequency to reconsider their habits. Offsetting the timing when agents re-consider their TMs is also beneficial for model results as it is assumed that the time when a person re-considers their TMs choice is independent of other agents' timing.

Past Experience

During a habit cycle (whenever the agent does not reconsider their mode), agents make either negative or non-negative experiences with their current TM, depending how crowded they perceive the TM. Whether an agent experiences a TM as crowded is modelled using a sigmoid function which returns the probability that the agent makes a negative experience as a function of the ratio of the count of other users using their TM compared to the total number of agents. The probability is modelled with the formula:

$$P_{\text{crowdedness}} = \frac{1}{1 + e^{-20\left(\frac{N}{M} - \Theta\right)}}$$

With

N being the numbers of agents using the same mode globally during that time step,

M referring to the total number of agents, and

Θ being the *crowdedness midpoint* defined as a model input parameter. The midpoint defines the value, at which the agent has a 50% chance of having a negative experience.

When the agent's habit cycle has passed, whether the agent evaluates the TM as *too crowded* is determined with probability

$$P_{too\ crowded} = \frac{Number\ of\ crowded\ experiences}{Number\ of\ total\ experiences}$$

If the TM is considered *too crowded*, it is temporarily removed from the agent's *available modes* for their next TM choice. It will also negatively impact the weight the agent has for that TM, which will be elaborated on in the submodule *learning.*

TM choice

The agent chooses their next TM. The agent's mode is randomly drawn from the agent's *available modes* with weights defined by the agents *tm_weights.*

Social Pressure

Agents check which TM was most chosen by agents in their social network. Should two TMs be equally popular, it is randomly determined which TM they consider as popular. Whether they perceive the number of agents within their social network choosing that TM as *social pressure* is modelled by a sigmoid function, similar to how *crowdedness experience* is modelled. The probability of experiencing *social pressure* is defined by

$$P_{\text{social\_pressure}} = \frac{1}{1 + e^{-20(\frac{N}{M} - \Theta)}}$$

With

N being the number of agents in their social network using the most used mode,

M being the total number of agents in their social network,

and Θ being the midpoint defined by *social_midpoint.*

If the agent feels social pressure, and only if the respective TM is within the agent's *available modes*, then the agent has a chance $P_{social\ adaptation}$ = 80% of adapting their chosen TM to the social norm. An agent adjusting to the social norm will disregard the TM chosen during the *TM choice* phase and choose the social norm TM instead. Adjusting also permanently increases the agent's weight for the TM, which will be further explained under *learning.*

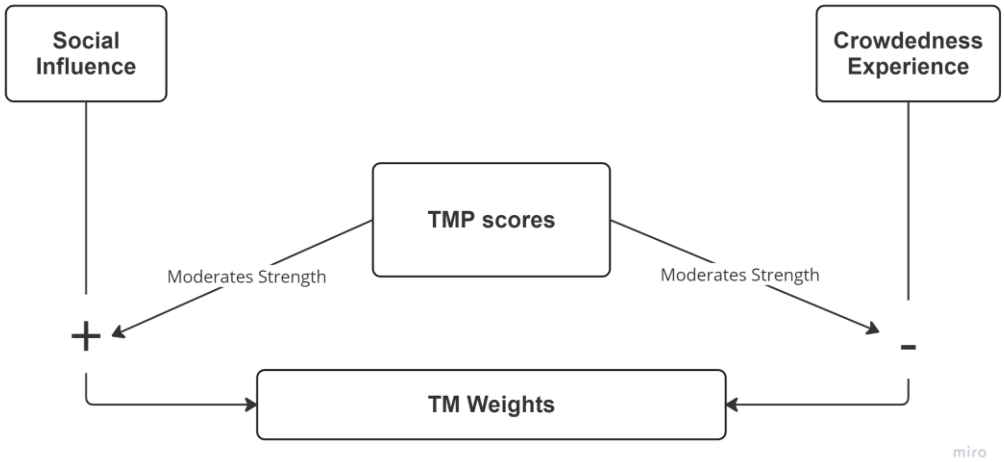
Agents' perception of *social pressure* was modelled as a sigmoid function to account for variability in individuals' likelihood of adapting to social trends. In line with Köckritz et al. (2023), an additional stochastic element was used with the 80% chance of adopting to the mode to account for various external reasons which could stop an agent from complying to their social environments' choices.

Learning

The agent's weights are permanently changed when they perceive a TM as *too crowded* or when they perceive *social pressure.* How strongly the weight of the affected TM is adjusted depends on the model parameter inputs *social influence, crowdedness influence,* and *TMP impact,* and on the agent's TMP score for the given TM. Experiencing the TM as *too crowded* will lower the TM weight while experiencing *social influence* will lead to an increase. Both effects are moderated by the agents' TMP score, as shown in Figure 6.

Figure 6

Dynamics determining TM weight adjustments



Note. TM Weight increase after experiencing social influence and decrease after experiencing crowdedness. The magnitude of the changes gets moderates by the TMP score, with higher scores increasing the positive effect of social influence and decreasing the negative effect of crowdedness.

If the agent experiences *social pressure* for a TM*,* their new *TM weight* for that TM is calculated:

$$\text{TM Weight}_{\text{pressured}} = \text{TM Weight}_{\text{old}} * (1 + \textit{social influence} * \textit{TMP\_moderator}),$$

With

Social influence being determined by the model parameter input *social influence*, and

$TMP\_\ moderator = (|tmp_{TM}| / max\_tmp) * (tmp\_impact – 1) + 1$ if $tmp_{TM} > 0,$ and

$TMP\_\ moderator = 1/((|tmp_{TM}| / max\_tmp) * (tmp\_impact – 1) + 1)$ if $tmp_{TM} < 0.$

With

tmp_{TM} being the TMP score of the pressured TM,

And $max\_tmp = 120,$ the maximum possible *tmp score*.

For the affected TM, this computation increases the TM weight based on the model parameter *social influence.* How large the increase is, is moderated by the agents *tmp score* and consequently the *tmp moderator*. With *tmp* scores having a possible range of -120 – 120, the *tmp moderator* yields a factor > 1 for *tmp scores* > 0 and a factor < 1 for *tmp scores* $< 0.$ The model parameter input $tmp\ impact = x$ influences the margins of the factor, with the lowest possible *tmp score* resulting in a *tmp moderator* =

1/x and the highest possible *tmp score* resulting in a *tmp moderator = x.* The models default value for *tmp impact = 2* can therefore up to double the effect of *social influence* for a *tmp score* = 120 and half it for a *tmp score* = -120.

Similarly, experiencing *crowdedness* decreases the agents weight of the affected TM, but higher *tmp scores* buffer the negative effect. The new TM weight is calculated with

$\text{TM Weight}_{\text{crowded}} = \text{TM Weight}_{\text{old}}$ *

With

crowdedness influence being the model parameter input *crowdedness influence*.

Here, a higher value for *tmp moderator* decreases the value of the denominator thereby causing less of a decrease of the TM weight.

This implementation fosters an interaction between the agents internal attitudes towards the TM (tmp scores) and external influences (social influence and crowdedness experience). Agents with more negative attitudes towards a TM are less affected by positive external influences compared to agents with positive attitudes. Likewise, more positive attitudes increase the likelihood of being influenced by positive external influences and make the agent more resistant to being negatively affected.

Sensitivity Analysis

We run a sensitivity analysis to identify the most relevant parameters driving model outcomes and assess model stability. As suggested by Broeke et al. (2016), we first run a one-factor-at-a-time (OFAT) sensitivity analysis to explore how individual parameters affect model outcomes. We follow this up with a global sensitivity analysis (GSA) to investigate interaction effects between parameters.

For the GSA, a density-based PAWN analysis was chosen, as it is more flexible towards outcome distributions compared to variance-based GSA (Pianosi & Wagener, 2015; Pianosi & Wagener, 2018).

Parameter Inputs

During model development and pre-runs, a selection of parameters for variation in the sensitivity analyses was made based on both their impact on model outcomes and their significance on model interpretation and potential implications of the results. *Crowdedness influence* and *crowdedness midpoint* were chosen as their influence on outcomes would stress the importance of affordances and TM capacities of the individual's environment. *Social Influence* and *Social midpoint* would show the relevance of social norms and their internalisation, and *TMP impact* represent the impact of agents internal attitudes towards TMs.

For these five parameters to be varied, default parameters were set as shown in Table 3. Pre-runs also indicated that 1000 steps per model run would be needed to assess whether the model achieves a balanced state, if yes, what the TM counts of the final model state are.

Table 3

Default Model Parameter Input

Parameter	Value Input
Crowdedness Influence	0.1
Social Influence	0.1
Crowdedness Midpoint	0.5
Social Midpoint	0.5
TMP Impact	2

For the OFAT analysis, input values were chosen as shown in Table 4, leading to a total of 48 model initiations. The GSA PAWN analysis was run based on 384 samples from parameter ranges shown in Table 5.

Table 4

Input Values used during OFAT

Parameter varied	Input range	Steps	Total initiations
Crowdedness Influence	0.0 – 0.45	0.05	10
Social Influence	0.0 – 0.45	0.05	10
Crowdedness Midpoint	0.3 – 0.75	0.05	10
Social Midpoint	0.3 – 0.75	0.05	10
TMP Impact	1 – 4.5	0.5	8

Note. The column 'steps' refers to the difference between values within the input range.

Table 5

Parameter Input Ranges for PAWN Global Sensitivity Analysis

Parameter	Value Range
Crowdedness influence	0.0 – 0.3
Social influence	0.0 - 0.3
Crowdedness midpoint	0.3 – 0.7
Social midpoint	0.3 – 0.7
TMP impact	1 - 5

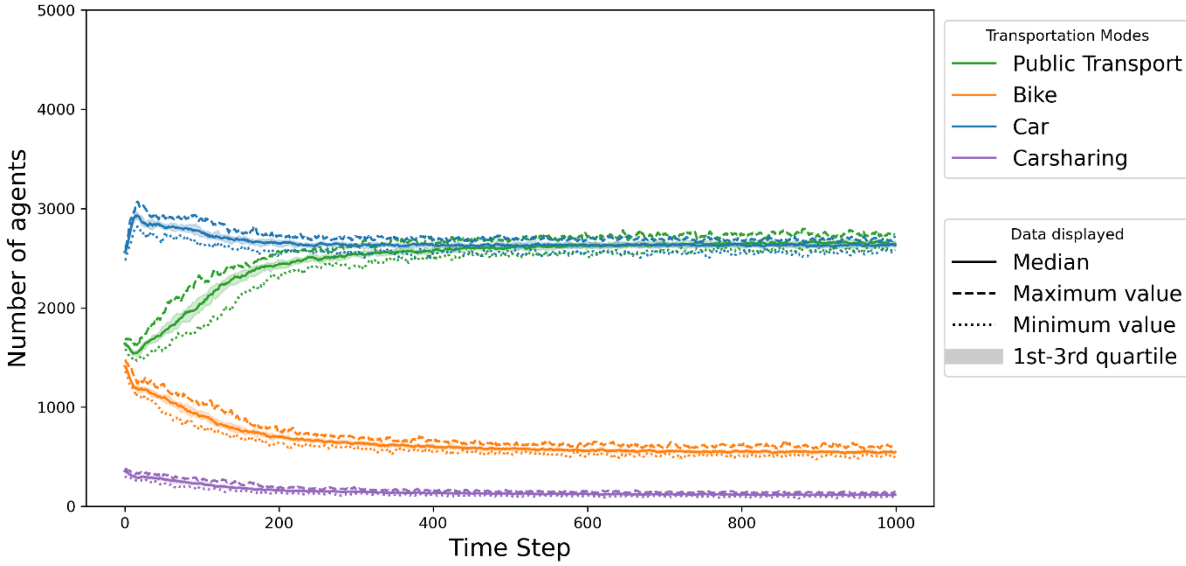
As primary outcomes of interest, the number of car users in the final state of the models is considered, as well as the variation of car user count within initiations. In the GSA as PAWN analysis is run on both the final car count mean and standard deviation (SD) of model initiations. PAWN indices indicating the relative impact of each parameter on the mean and SD, respectively. For both the OFAT and GSA, further testing and visualisation of individual runs will be applied in an explorative manner for model initiations which show deviant outcomes.

Results

The results with default parameter input show that the model converges into a balanced state after approximately 500 steps, as shown in Figure 7. During step 1 of the model, car counts (m = 2563, iqr = 43.25, max = 2604, min = 2485) is much higher than public transport counts (m = 1638.5, iqr = 38.75, max = 1682, min = 1577) and the gap increases until step 40, where car counts reach a peak (m = 2835, iqr = 50.75, max = 2939, min = 2732). At step 500 car counts (m = 2629, iqr = 35.5, max = 2693, min = 2561) and public transport counts (m = 2605, iqr = 52, max = 2676, min = 2525) are approximately even and remain in that state for the remaining steps. The TM bike starts with a similar count (m = 1410, iqr = 39.25, max = 1472, min = 1353) and then decreases first steeply until it fades out around step 500 (m =580, iqr = 25.75, max = 616, min = 540). Carsharing has low usage counts throughout the model and decreases slightly from step 1 (m = 356, iqr = 30.5, max = 376, min = 296) to step 500 (m = 127, iqr = 17, max = 150, min = 105). After step 500, few changes in TM counts happen and the model remains in a balanced state for the remaining steps.

Figure 7

Model result with default parameter inputs



The figure displays the number of each TM chosen at each step of the model. For each TM, the median, maximum, minimum, and interquartile range are displayed.

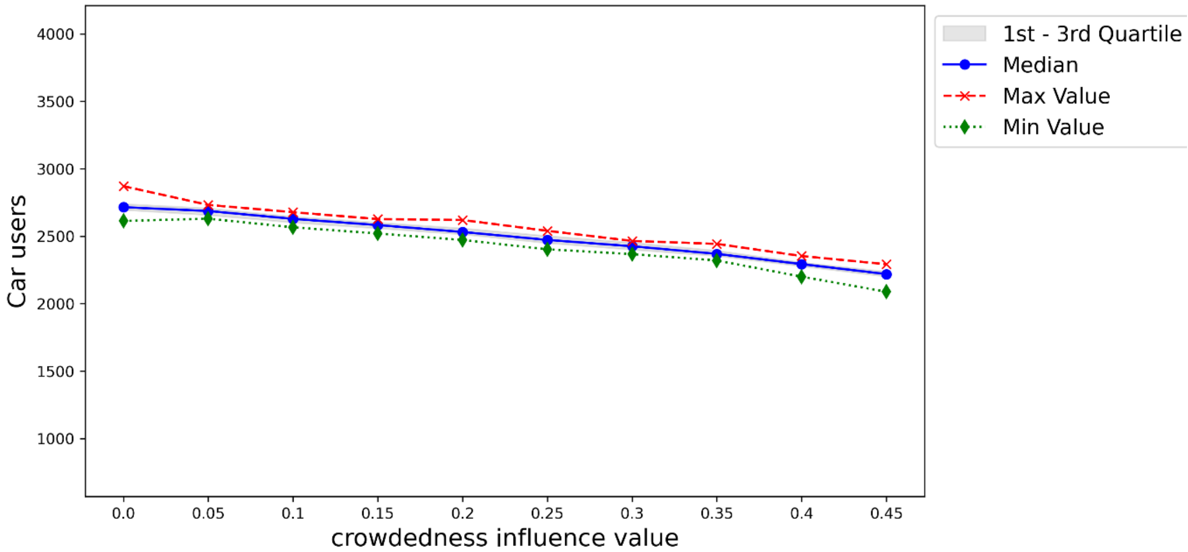
Results on the influence mechanisms *social influence* and *crowdedness* show that agents experienced both most frequently for the TM car ($n_{social\ influence}$ = 2715800, $n_{crowdedness}$ = 2519403), followed by public transport ($n_{social\ influence}$ = 3274069, $n_{crowdedness}$ = 1846000), bike ($n_{social\ influence}$ = 7456, $n_{crowdedness}$ =1745) and carsharing ($n_{social\ influence}$ = 0, $n_{crowdedness}$ = 49).

One-factor-at-a-time sensitivity analysis

OFAT results for C*rowdedness influence* are shown in Figure 8. From the c*rowdedness influence* = 0.0 (*m =2715, IQR =43, max =2871, min =2613*) to c*rowdedness influence* = 0.45 (*m* =2219*, IQR* =35.25*, max* =2292*, min* = 2088) a continuous decrease in car counts can be observed with higher values for *crowdedness influence*. No significant changes in the interquartile range and distance between minimum and maximum values are found.

Figure 8

Counts of Car Users per crowdedness influence initiation

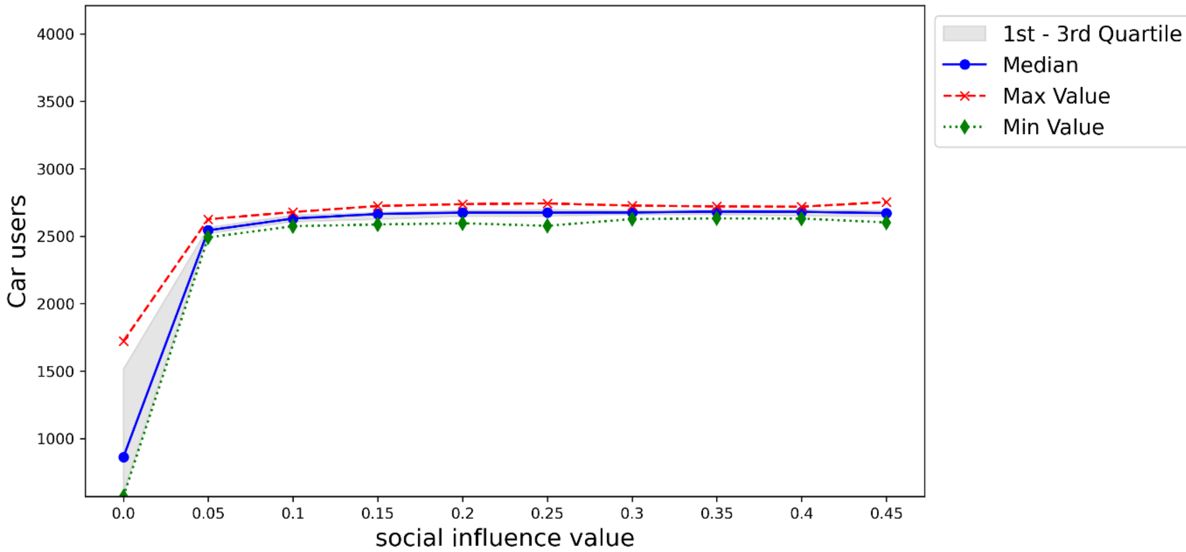


The figure displays car counts (median, maximum, minimum, IQR) of the final model step on the y axis, the varied parameter input is displayed on the x axis.

OFAT results of *social influence* are displayed in Figure 9. A major increase in car counts can be observed between *social influence* = 0.0 (*m* =862.5*, IQR* = 920.75, *max* =1722*, min* =570) and *social influence* = 0.05 (*m* =2543.5*, IQR* =45.25, *max* =2626*, min* =2491). The remaining parameter inputs between 0.05 and 0.45 (*m* = 2671.5*, IQR* =41.75*, max* =2753*, min* =2602) yield relatively similar results. Similarly, the variance in outcomes for *social influence* = 0.0 is larger than for all other *social influence* initiations.

Figure 9

Counts of Car Users per social influence initiation

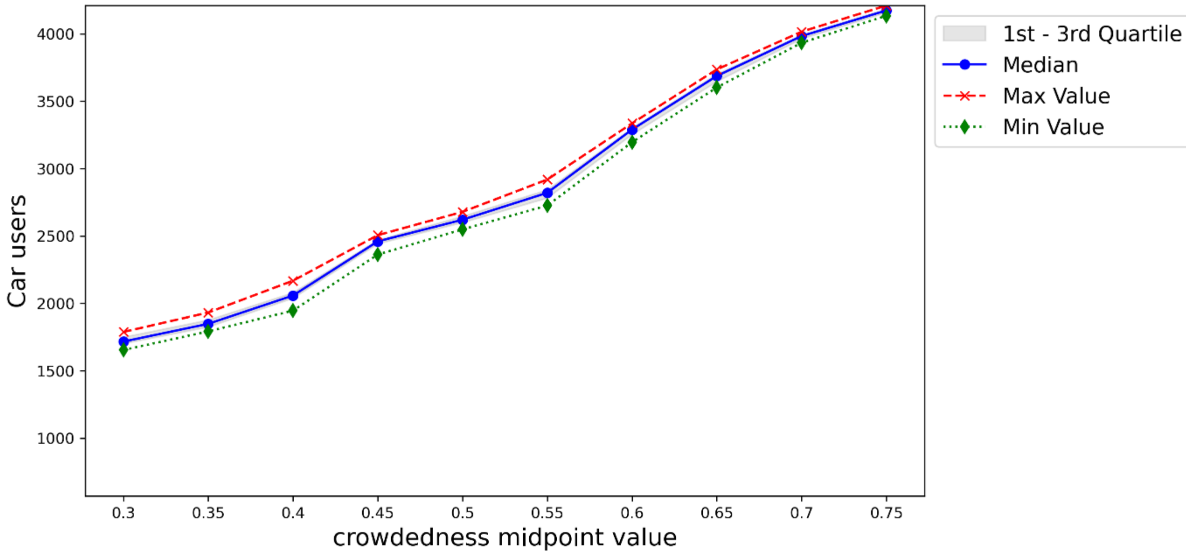


The figure displays car counts (median, maximum, minimum, IQR) of the final model step on the y axis, the varied parameter input is displayed on the x axis.

Varying the midpoint of the *crowdedness midpoint* parameter significantly changed the model outcomes, as shown in Figure 10. While with *crowdedness midpoint* = 0.3 (*m* = 1716.5*, IQR* = 47.5*, max* =1788*, min* =1654) car counts are lower compared to other initiations, with *crowdedness midpoint* = 0.75 (*m* =4173.5*, IQR* = 26.5*, max* = 4210*, min* =4134), car counts are more than twice as high. Interquartile range and maximum and minimum values show no significant differences.

Figure 10

Counts of Car Users per crowdedness midpoint initiation

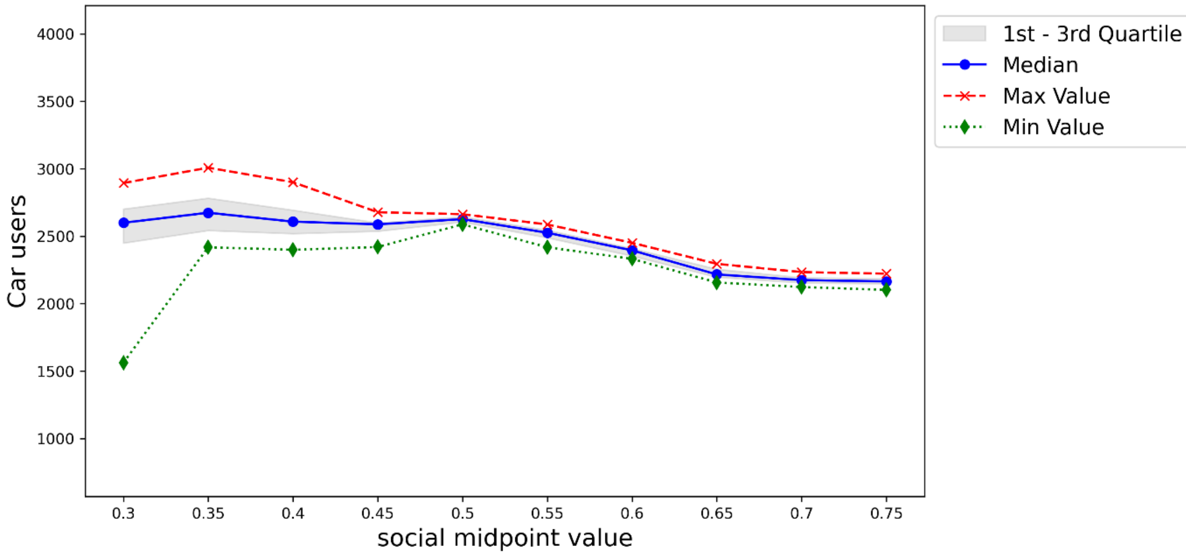


The figure displays car counts (median, maximum, minimum, IQR) of the final model step on the y axis, the varied parameter input is displayed on the x axis.

Opposed to the increase in car counts with increased *crowdedness midpoint* parameter input, car counts decrease with higher inputs for the *social midpoint* parameter, as shown Figure 11. With *social midpoint* = 0.3, car counts have a median(*m*) of 2599.5, *IQR* = 252.5, *max* =2894, and *min* =1562. With the maximum input of *social midpoint* = 0.75, car counts are significantly lower (*m = 2165, IQR* =37*, max* =2222*, min* =2102). Notably, the variance in car count outcomes gets significantly lower with increasing *social midpoint* inputs.

Figure 11

Counts of car users per social midpoint initiation

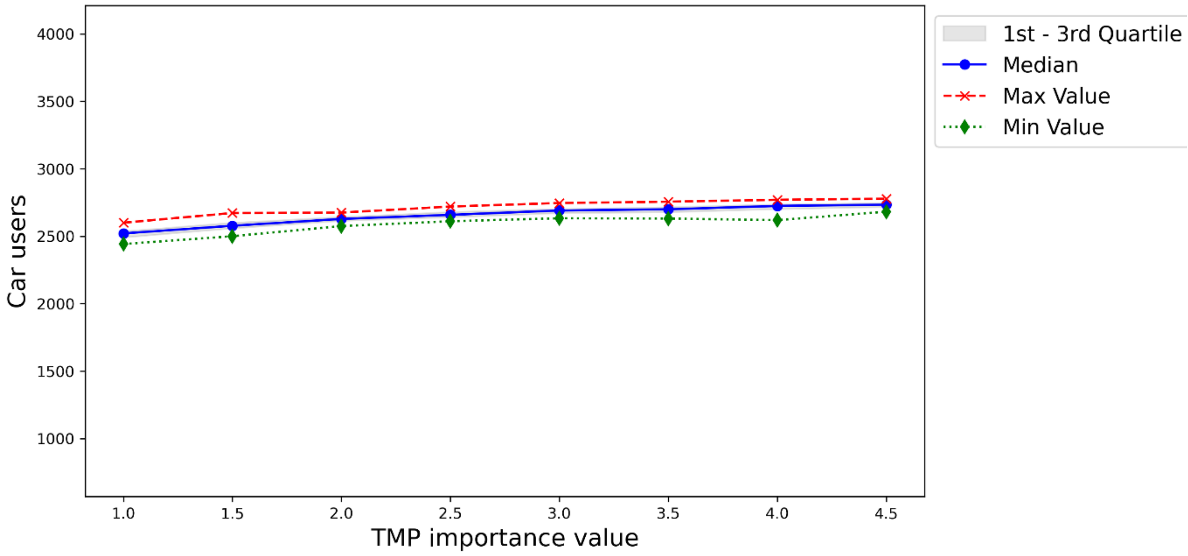


The figure displays car counts (median, maximum, minimum, IQR) of the final model step on the y axis, the varied parameter input is displayed on the x axis.

The final varied parameter in the OFAT analysis is *TMP impact.* As shown in Figure 12, car counts do barely differ between *TMP impact* = 1 (*m* =2520.5*, IQR* = 45*, max* =2600*, min* = 2442) and *TMP impact* = 4.5 (*m* =2733.5*, IQR* = 28.75, *max* = 2778*, min* = 2682), but there is a slight increase in car counts with higher *TMP impact* inputs.

Figure 12

Counts of car users per TMP impact initiation



The figure displays car counts (median, maximum, minimum, IQR) of the final model step on the y axis, the varied parameter input is displayed on the x axis.

Global Sensitivity Analysis

The PAWN analysis on relative importance of parameters was run twice, once for the mean car counts and once for the standard deviation (SD) of car counts to assess the variance of model outcomes. The analysis yields a median PAWN index for each parameter, indicating the relative importance of that parameter on the model outcomes of interest (mean car counts or SD of car counts).

Crowdedness midpoint is the most important parameter (*PAWN index* = 0.469) in determining the mean car counts value in a model initiation, followed by *social influence* (*PAWN index* = 0.25). Looking at the SD of car counts, *social midpoint* has the largest influence (*PAWN index* = 0.54). More details on the PAWN scores for each parameter are displayed in Table 6.

Table 6

Sensitivities based on PAWN GSA Indices for Mean and Standard Deviations of Car Counts

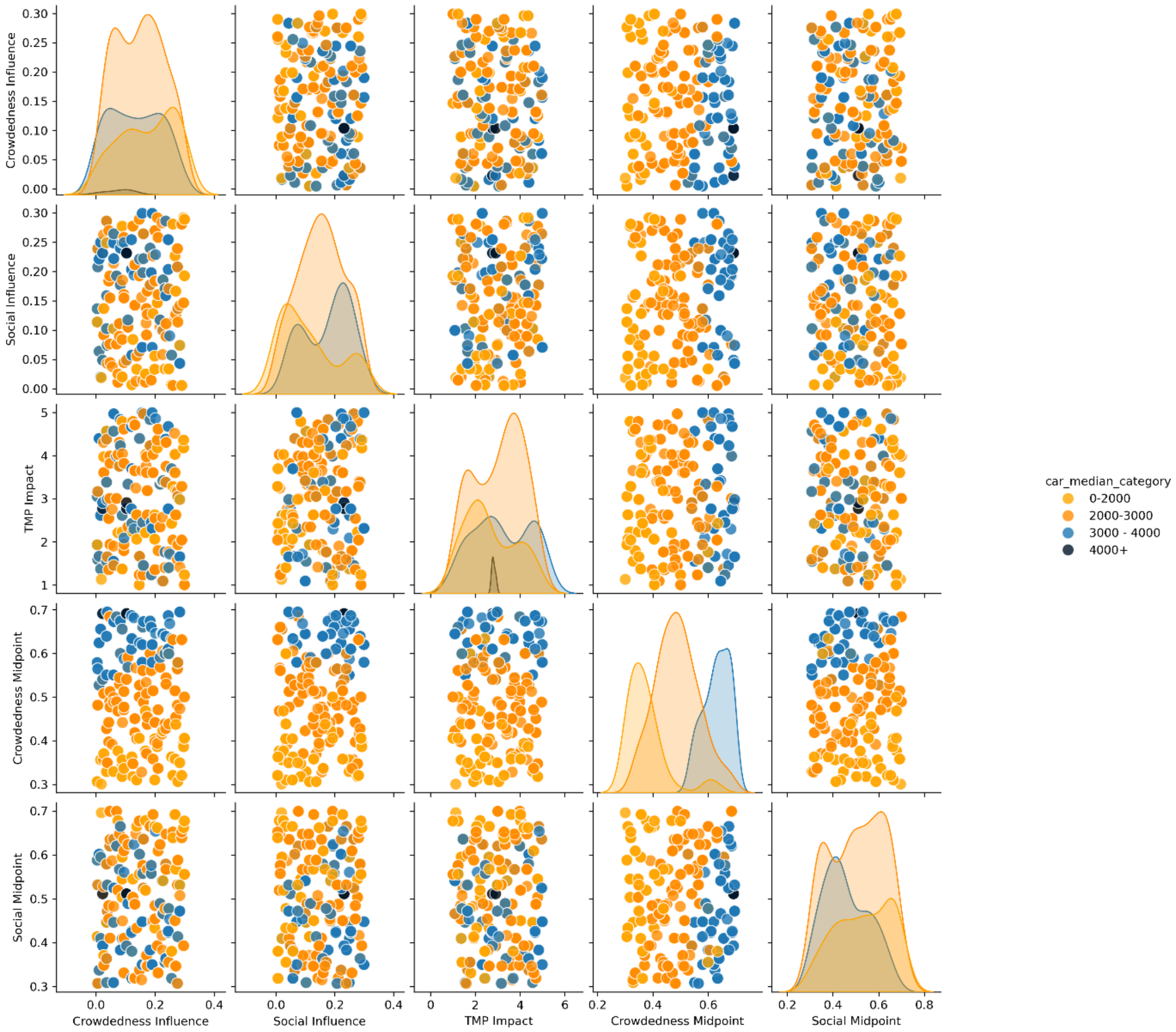
Parameters	**Index for Mean Car Counts**	**Index for Variability (SD) of Car Counts**
Crowdedness Influence	0.17	0.16
Social Influence	0.25	0.21
Crowdedness Midpoint	0.49	0.15
Social Midpoint	0.19	0.54
TMP Impact	0.23	0.20

Note. The PAWN index shows the relative importance of each parameter on the relevant outcomes the parameter has on the model outcome.

Investigating possible interaction effect, visual analysis suggests an interaction between *social* midpoint and *crowdedness midpoint,* as shown in Figure 13. A higher value for *crowdedness midpoint* is associated with higher car counts, but the effect appears stronger with lower values for the *social midpoint* parameter.

Figure 13

Pairwise Interactions Effect of Parameter Inputs on Car User Count



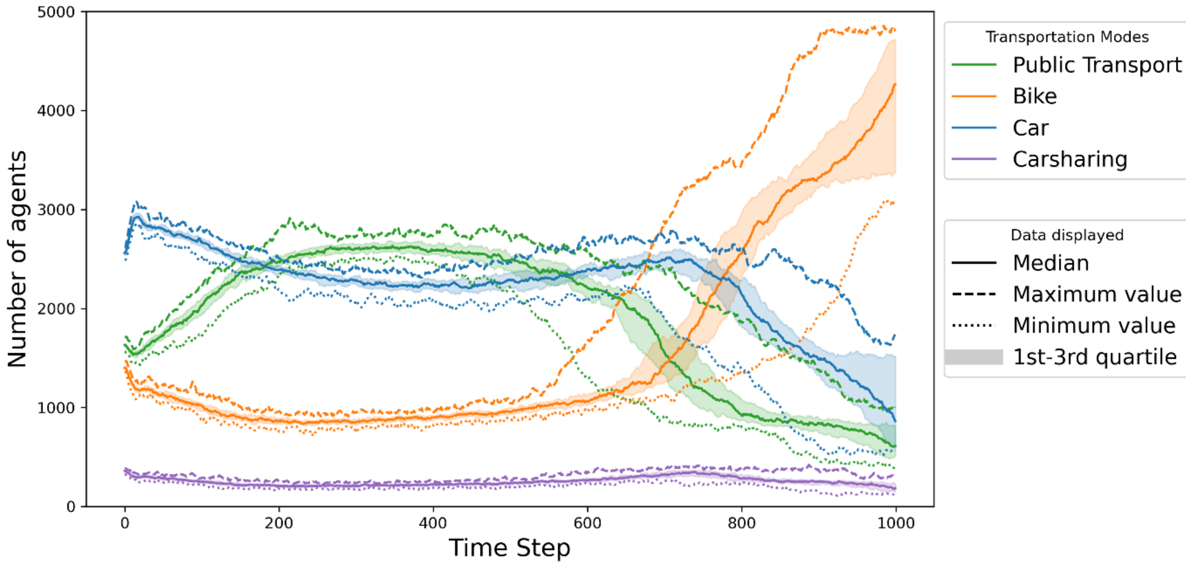
The figure shows count of cars in the final model state by pairwise combination of model parameter combinations. Each point represents a model initiation, with the colour determining the median car counts and the position showing the combination of parameter inputs of the respective two parameters on the y and x axis.

Exploratory analysis

Based on sensitivity analyses results, specific model parameter combinations were explored in more detail. As observed in the OFAT on *social influence*, car counts were low for *social influence* = 0.0 compared to other initiations. In the absence of *social influence,* the TM car is initially most dominant. Public transport counts increase and become the most used TM for the early to mid-stages of the model (step 185 – 577), with car being the most used mode again during the late mid-stage of the model (step 577 - 777), and bike being the most used for the end stage of the model.

Figure 14

Counts of car users with social influence parameter = 0.0

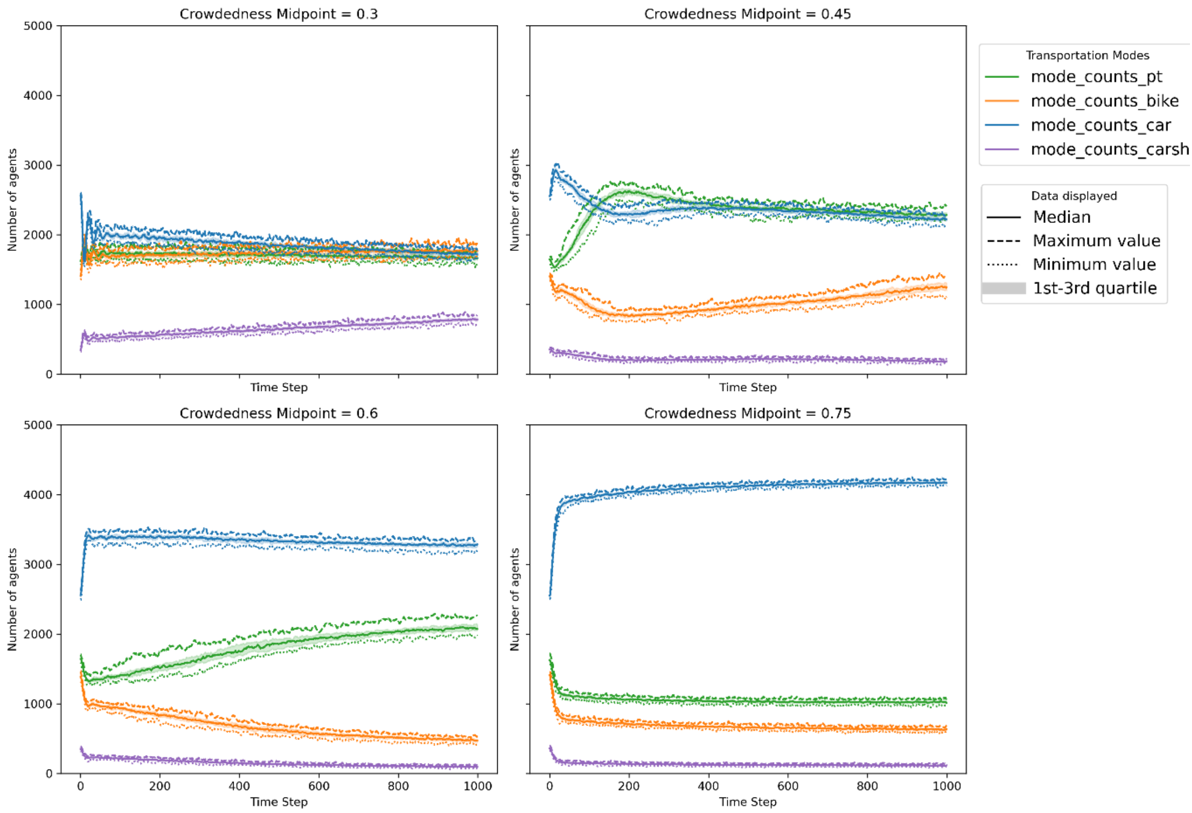


The figure displays car counts (median, maximum, minimum, IQR) of the final model step on the y axis, the varied parameter input is displayed on the x axis.

Further, the parameter *crowdedness midpoint* had the largest influence on car counts, as indicated both by OFAT and GSA. As shown in Figure 15, car usage throughout the model steps is higher with higher values for *crowdedness midpoint.* For *crowdedness midpoint* = 0.3, all alternative TMs increase over time and car, public transport, and bike develop to having similar counts in the later stages of the model. For *crowdedness midpoint* = 0.45, only public transport is even with car counts, and for *crowdedness midpoint* > car is the most used TM, with higher *crowdedness midpoint* value initiations having more substantial differences between car and competing modes.

Figure 15

Effects of Crowdedness Midpoint Variations



Subplots display model results for crowdedness midpoint = 0.3, 0.45, 0.6, 0.75, from top left to bottom right. Each plot displays car counts (median, maximum, minimum, IQR) of the final model step on the y axis, the varied parameter input is displayed on the x axis.

Discussion

Our study implemented an agent-based model to explore dynamics that could lead to lower-emission transportation mode (TM) choices. We advanced the TransportTransform model created by Köckritz et al. (2023) by implementing mechanisms in which agents learn from their experiences and adapt their preferences. We further implemented internal attitudes towards TMs as a moderator of influenceability. Finally, one factor at a time (OFAT) and PAWN global sensitivity analysis techniques were applied to investigate the function of model parameters and explore model outcome differences to answer the research question.

Our model results with default parameters show that TM choices do change over time. While the car is the most frequently used mode during the starting phase of the model, over time the model stabilises in a state where public transport and the car are used equally frequenty. However, the number of car users does not significantly decrease. Rather, bike users decrease with increasing public transport users, suggesting that people switch from biking to using public transport. This is a surprising result because overall TM attitudes from the initiation data by Wolf & Schröder (2019) were higher for the bike compared to public transport. By the conception of the model, this leads to greater increases in bike preferences compared to public transport preferences upon experiencing the TM as a social norm, and to smaller decreases in bike preferences compared to public transport preferences upon experiencing the TM as crowded. An explanation for this emergence is that during the first steps, public transport was the second most popular TM after car and therefore more popular than biking. Consequently, biking was rarely considered popular in the social environment, leading to few positive adjustments of agents' preferences towards the bike. In a future model version, more extensive test runs with different starting preferences and TM count distributions could be performed to further analyse the effects of TM use distributions during the first model steps. A possible implication of these findings is that a TM must reach a degree of popularity before it can grow through the effects of social influence. In cases in which it is desired to grow an unpopular TM, efforts relying on other mechanisms may be needed to reach that popularity.

Our Sensitivity analysis yielded interesting results regarding the role of TM crowdedness, with the varied parameter *crowdedness midpoint* being a key determinant of car users in the final model state. The *crowdedness midpoint* parameter can be interpreted as a measure of crowdedness tolerance. In our model results, lower crowdedness tolerance results in similar numbers between car, bike, and public transport users, as well as increases in carsharing counts. The results further show that use counts of the most popular TM at the model start, the car, adjust to the percentage of the parameter input. If the crowdedness tolerance is higher, car users continuously increase until a number of car users is reached with which people start perceiving the mode as crowded. This happens because social norms reinforce the most popular TM most until there is a reason not to use it anymore. In the context of the goal of decreasing the number of car users, this finding stresses the importance of people's sensitivity towards crowdedness perception. While the perception of crowdedness by influencing people's crowdedness sensitivity might be impractical, crowdedness perception could indirectly be influenced by the infrastructure capacities the TM provides. Changes in capacity were not a part of our model and would be an interesting option to explore in a future version. However, our findings stress the relevance of crowdedness perception in TM choices. Reducing the capacity for cars while increasing the capacities for alternative TMs would indirectly affect how soon individuals perceive a TM as crowded and could thereby contribute to more people considering alternatives to using the car.

A related concept, the degree to which experiencing crowdedness negatively influenced an agent's preferences was the parameter *crowdedness influence.* A small decrease in agents using the car in the final model step was found. Assumably because the car is the most popular mode, agents' preferences for cars were most often negatively affected. However, in comparison to changes in how soon agents experienced a TM as crowded (variation of *crowdedness midpoint*), the differences are negligible. These findings suggest that the frequency of crowdedness experience rather than the degree to which one experience affects an individual was crucial for determining car choices long term.

Social norms are another factor influencing car usage in our model. Car counts in the final model state are rather similar for different strengths of social influence but are significantly lower in the absence of social influence. Considering the mechanisms of our model, this finding might be caused by a lack of positive reinforcement on TM weights given the lack of social influence. With cars being the most used TM initially, car users are most punished by the negative feedback mechanism of crowdedness, thereby making the TM car less preferable over time. Interpreting this finding, our results stressed the importance of social norms and reinforcement between car users. With many people frequently using the car, as evident in Wolf & Schröder (2019), it is also the social norm in most social circles. This interpretation is in line with our findings on varying the parameter *social midpoint*. This parameter can be interpreted as the average percentage of an individual's environment that is needed to create the perception of a social norm. Lower percentages lead to higher variance in car users, and more model runs resulted in public transport being more popular than cars compared to higher percentage model initiations because more sub-populations formed that were using alternatives to the car. This finding suggests that if the perception of a social norm can be formed based on a lower (population) percentage, alternatives to the TM car have a higher probability of becoming popular. While it is difficult to influence an individual's 'threshold' on how soon they perceive TM choices as a social norm, the emergence of sub-populations using alternatives might be an addressable factor in practice. Spreading the existence of TM alternatives and making the number of people using them as visible as possible, e.g. through media or advertisements, could therefore increase the positive effects of social norms on car alternatives and thereby reduce the use of cars.

Limitations & Future Research

Several limitations need to be considered when interpreting our findings. First, our model may be limited in modelling environmental affordances, as discussed by Kaaronen and Strelkovskii (2020). While having a driver's license and owning a car afford the TMs car and carsharing, other affordances could be considered in people's individual environments. For example, it could be argued that the distance to the next public transportation station or the availability of bike lanes in the neighbourhood affords public transport or biking, respectively. The lack of these mechanisms may have led to our model results overestimating the use of public transport and biking.

Second, in our model, we assume that crowdedness perception equally applies to all TMs. Scenarios are imaginable for all TMs, such as being stuck in traffic, having to stand in an overcrowded bus or tram, cycling in a busy cycling lane, or having to wait or walk further for the next available carsharing vehicle. However, it remains unclear if all TMs have the same function of becoming increasingly dissatisfying with higher numbers of people using them. Our model, assumes this, though a case could be made that for example biking is a TM that might be less affected by negative experiences due to crowdedness.

Related to both limitations above, our model does not directly consider the capacities of TM infrastructures. TM capacities might be a crucial factor as physical environments significantly differ in the extent of the public transportation network, road and bike lane infrastructure, and carsharing service availability. It could be argued that capacities differ depending on the location, and tipping points of TMs being perceived as too crowded are affected. While adding different locations with different TM capacities would perhaps add (too) significant complexities to the model, not considering TM capacities at all could be considered an oversimplification.

For future research and model versions, it might be interesting to include characteristics of different physical environments with different TM capacities and a larger selection of factors determining affordances. This model extension would also allow for experimenting with changes in capacities for specific physical environments, thereby increasing the relevance of findings for policy advising and TM infrastructure extension projects.

Conclusions

Our results indicate that reducing the number of car users is possible under the right circumstances. As the most popular TM, car users increase through reinforcement of social norms until a threshold is reached where the perception of crowdedness causes negative experiences when travelling by car. We show that higher sensitivity towards crowdedness perception leads more people to choose alternative TMs, thereby reducing the number of car users. We further stress the relevance of TM infrastructure capacities to influence people’s crowdedness perception of different TMs. In addition, social norms can foster the popularity of car alternatives in sub-populations. However, a certain popularity might be required for social norms to have a positive effect on car alternatives, and less popular TM alternatives might have to rely on other mechanisms to grow in popularity.

Further research is needed to fully understand the mechanisms that could lead to more sustainable transportation choices, with TM infrastructure capacities being a crucial factor to justify claims for the development of sustainable transportation options.

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Appendix A

Main extensions and changes in the current version compared to Köckritz et al. (2023)

Change	**Köckritz et al. (2023)**	**Current Version**
TM preference initialisation	Utilisation of 1st and 2nd preference based on empirical data, with 70% and 25% chance, respectively, and 5% for remaining available modes	Initialisation of TM weights based on reported frequencies of TM usage in the empirical data to more realistically simulate chances of picking TMs
TM Weights	Stable after initialisation	Weights dynamically update, experience of crowdedness reduces weights, experiencing social influence increases weights
Modelling social influence	Threshold function: if more than 50% of social environment use one TM, the agent has an 80% chance of adapting	Sigmoid function with midpoint being adjustable through model parameter *social_midpoint*
Modelling occupancy / crowdedness	Exploration of threshold & sigmoid function; removal of occupant/crowded mode from available modes if more bad than good experiences	Sigmoid function with midpoint being adjustable through model parameter crowdedness*_midpoint* to model experience, Removal of crowded mode from available modes with chance of $p = \frac{number\ of\ bad\ exerperience}{total\ number\ experiences}$
Learning	No learning implemented	Dynamic adjustment of TM weights based on model parameters *social influence, crowdedness influence, tmp impact*
Attitudes towards TMs	Not part of model	Computation of transportation mode potential (tmp) score based on respondents rating of TMs on transportation mode qualities and subjective transportation mode quality importance, integration of tmp scores as moderator on the effects of *social influence & crowdedness influence* on TM weights
Sensitivity Analysis	Technique: visual Parameters varied: Occupancy function (threshold/sigmoid),	Techniques: One-Factor-at-a-time & PAWN global sensitivity analysis

	occupancy module on/off, social module on/off	Parameters varied: *social midpoint, crowdedness midpoint, social influence, crowdedness influence, tmp impact*
N agents	1000 agents for majority of analysis, initiation based on sampling 1000 rows from empirical data	Initiation with full dataset (n = 5948)
Network creation	Random	Small world network[1]

Note[1]. Credit goes to my supervisor Luja von Köckritz